Regional Assessment of the Parameter-Dependent Performance of CAM4 in Simulating Tropical Clouds: Applying PCMDI Metrics to the UQ Ensembles

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Motivation

- Climate models often show different performance skills in simulating clouds over different regions
- Regional analysis helps identify model's strengths and weaknesses in simulating clouds over different climate regimes and therefore links model deficiencies to those physical processes that control these regimes

Objective

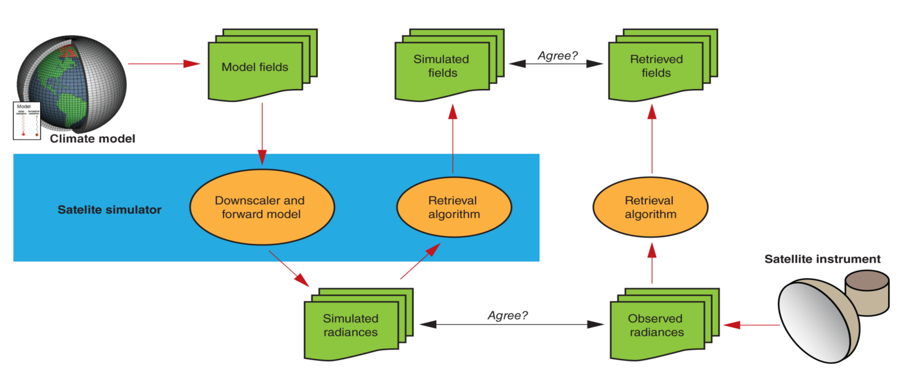
- Systematically examine the parameter-dependent performance of CAM4 in simulating clouds over different climate regimes
- Understand which parameters and their associated physical processes the simulations are most sensitive to

Analysis Methods

- Use the perturbed-parameter ensemble approach developed by the LLNL Climate Uncertainty Quantification (UQ) project.
- Apply PCMDI metrics used for multi-model assessments to the perturbed -parameter ensembles. Rank the ensemble members using the metrics and identify high performing members.
- Make use of cloud simulator output

Why Satellite Simulators?

- It converts model clouds into pseudosatellite observations with a model to satellite approach that mimics the satellite view of an atmospheric column with model specified physical properties.
- Facilitate a meaningful comparison of models with observations by accounting for limitations or features of the observing process



COSP – the CFMIP Observation Simulator Package

Development team :

- Met Office Hadley Centre
- LMD/IPSL
- Lawrence Livermore National Laboratory
- Colorado State University
- University of Washington

LLNL UQ Simulations

- The 57 OAT runs and 280 Latin Hypercube runs with 28 parameters perturbed from more than 1,600 twelve-year ensemble simulations of CAM4 are used in this study

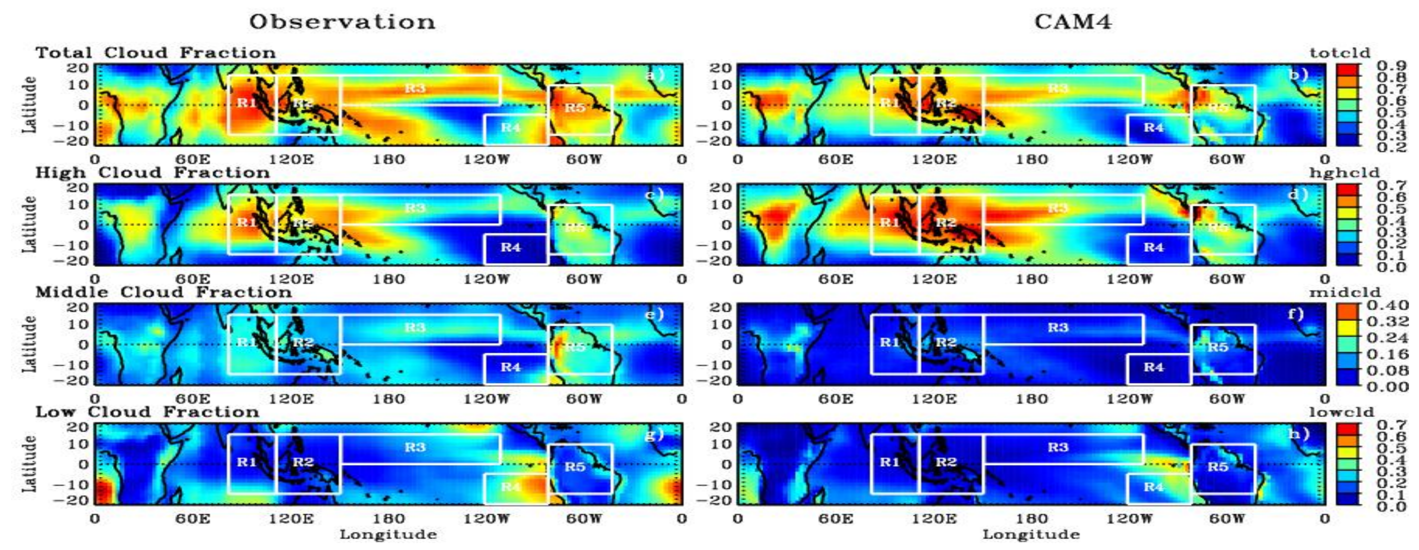
Note: OAT stands for one-at-a-time and the Latin hypercube runs pseudo-randomly sample the 28 parameters simultaneously.

rhminh	Threshold RH for fraction of high stable clouds	hkconv_c0	Shallow convection precipitation efficiency
rhminl	Threshold RH for fraction of low stable clouds	cmftau	Time scale for consumption rate of CAPE for shallow convection
rliqice	Effective radius of liquid cloud droplets over sea ice	alfa	Initial cloud downdraft mass flux
rliqland	Effective radius of liquid cloud droplets over land	zmconv_c0	Deep convection precipitation efficiency
rliqocean	Effective radius of liquid cloud droplets over ocean	dmpdz	Parcel fractional mass entrainment rate
ice_stokes_fac	Scaling factor applied to ice fall velocity	ke	Evaporation efficiency of convective precipitation
capnc	Cloud particle number density over cold land/ocean	tau	Time scale for consumption rate of CAPE for deep convection
capnsi	Cloud particle number density over sea ice	cdn_scal_fac	Ocean roughness scaling factor
capnw	Cloud particle number density over warm land	fac	ustar parameter in PBL height diagnosis
conke	Evaporation efficiency of stratiform precipitation	fak	Constant in surface temperature excess
icritc	Threshold for autoconversion of cold ice	betamn	Minimum overshoot parameter
icritw	Threshold for autoconversion of warm ice	z0m_scal_fac	Moisture & heat resistance to vegetation scaling factor
r3lcrit	Critical radius at which autoconversion becomes efficient	capelmt	Threshold value for CAPE for deep convection
ricr	Critical Richardson number for boundary layer	sgh_scal_fac	Land roughness scaling factor

Observations

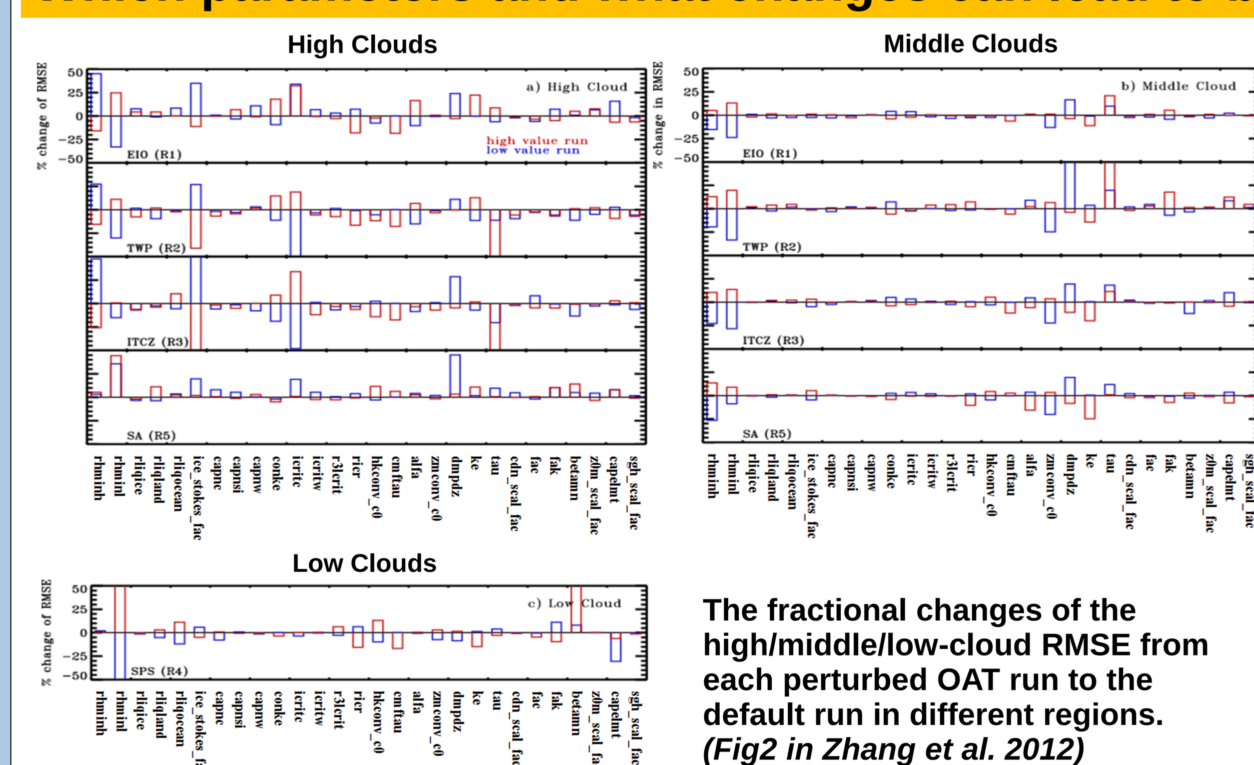
- GCM simulator-oriented ISCCP cloud product (July 1983 – June 2008)

Selected regions:



R1 – The Eastern Indian Ocean (Monsoon climate, high cloud fraction and rain rate)
R2 – The Tropical Western Pacific (Energy source region in the tropical circulation, warm temperatures and abundant rainfall)
R3 – The Pacific ITCZ (A band of clouds arising from deep convection)
R4 – The Southeastern Pacific Stratocumulus (A stratus cloud deck formed over cool surface water)
R5 – The South American Tropics (Tropical land with heavy rains)

Which parameters and what changes can lead to better model simulations?



The fractional changes of the high/middle/low-cloud RMSE from each perturbed OAT run to the default run in different regions. ***(Fig2 in Zhang et al. 2012)***

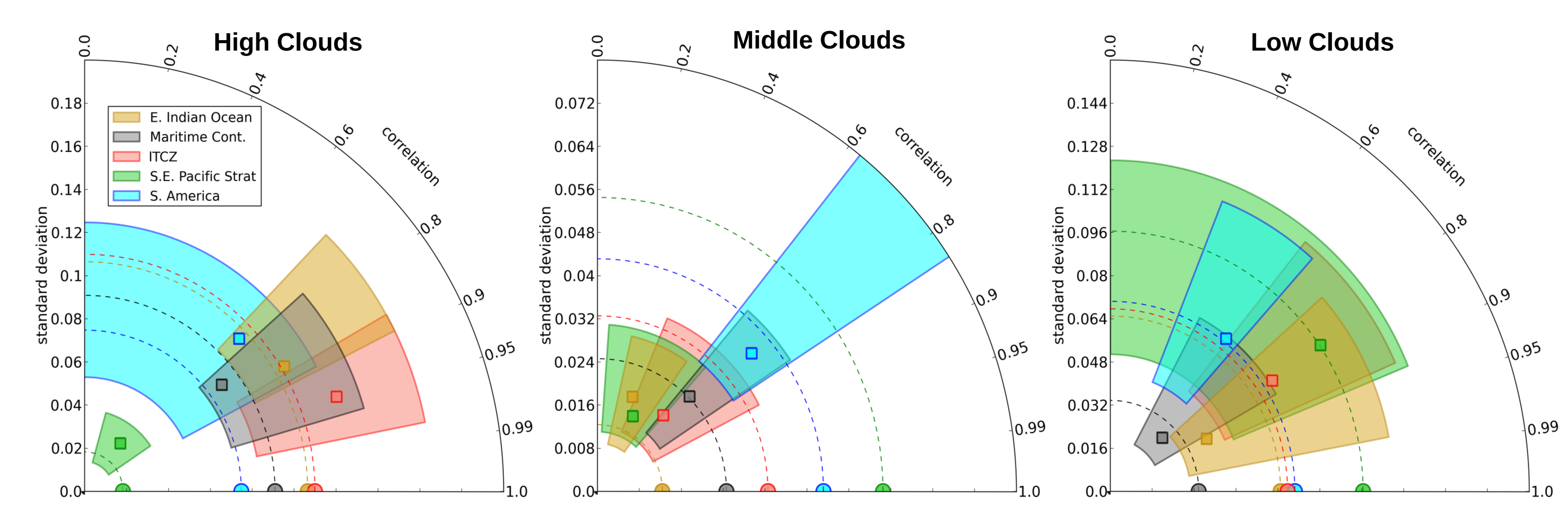
- ***The model performance is sensitive to parameters selected and varies with regions***
- ***Some improvements are cloud_type/region-dependent (e.g., 'rhminh', 'ke'). So an overall consideration of different cloud types over all regions is needed for model optimization***
- ***Some parameter setups could yield overall better simulations (e.g.,'rhminl', 'zmconv_c0'). Indicating cloud simulations might be improved by carefully adjusting these parameters***

Impact of nonlinear interactions among parameterized physical processes

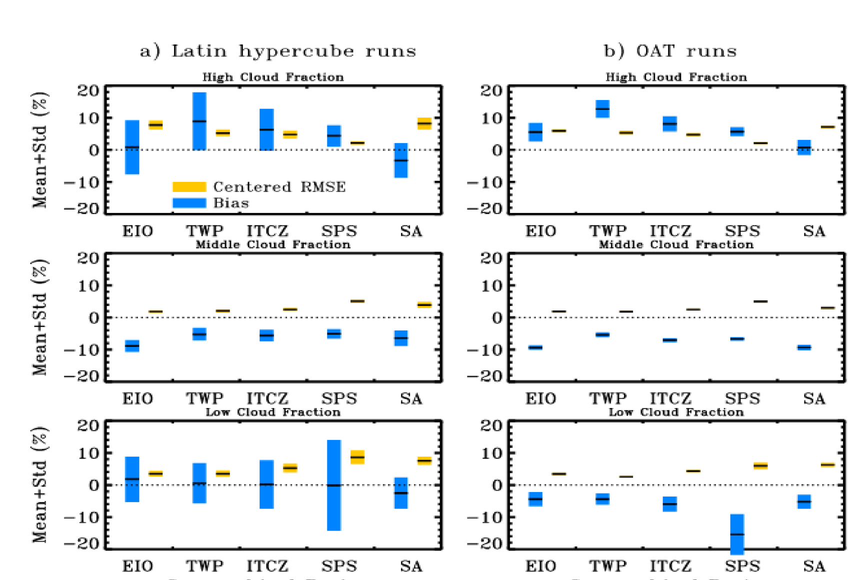
Three scalars included in Taylor Diagram

- **The radial distances from the origin to the points are equal to the pattern STDs.**
- **The azimuthal positions give the CC between the two patterns.**
- **The distance between a simulated field and the reference data is equal to their centered RMS diff.**

- ***For high clouds, it's difficult to capture cloud systems over the tropical land region***
- ***For middle clouds, the spatial pattern is less sensitive to the parameter changes***
- ***For low clouds, some of the perturbed runs produce more reasonable results over the Eastern Pacific***



Taylor diagrams of high/mid/low cloud fraction. Different regions are marked by different colors and the shaded domains are about 95% intervals (±2 sigma) of the 280 perturbed runs. The squares are the model default run and the half-circles are the reference data (observations). ***(Fig3 in Zhang et al. 2012)***



The mean and STD of the biases and centered RMSE of high/middle/low cloud fraction for different tropical regions from a) Latin hypercube runs and b) OAT runs. ***(Fig4 in Zhang et al. 2012)***

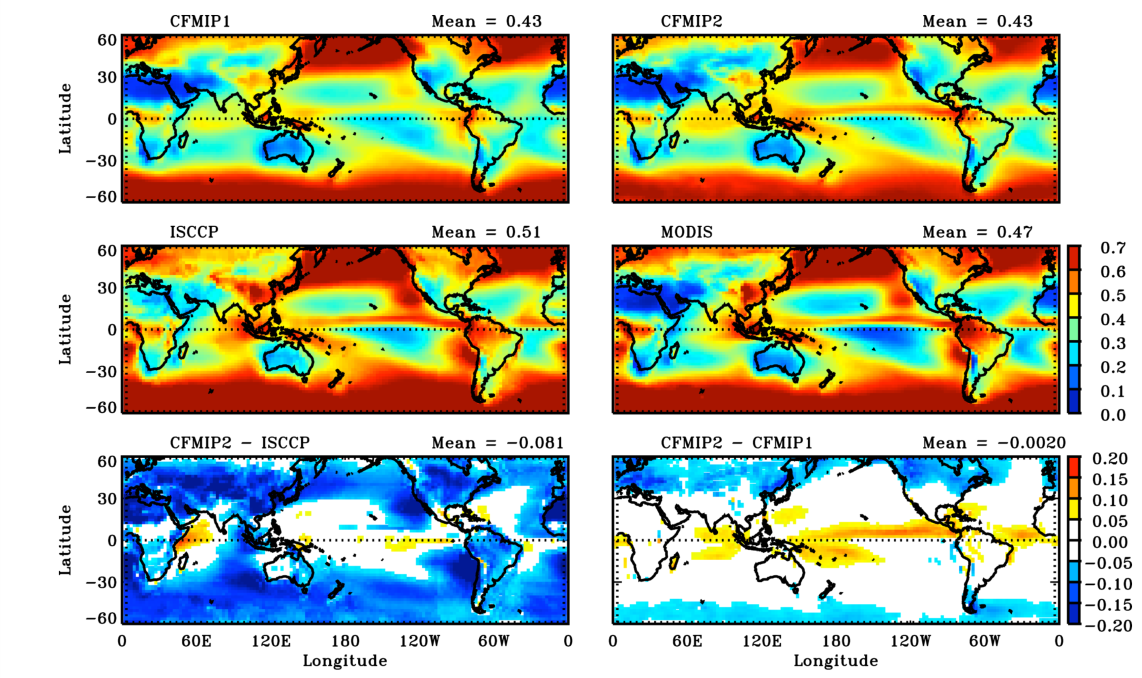
- **Centered RMSE in Taylor diagram represents spatial pattern error**
- **Bias defines the difference of area average**

- ***The large variation of bias indicates that the perturbed parameters have considerable effects on the simulations***
- ***The perturbed parameters have a larger impact on the mean bias than on the pattern error***
- ***Simultaneous adjustments of multiple parameters have more chances for the simulated cloud amounts to match the observations***

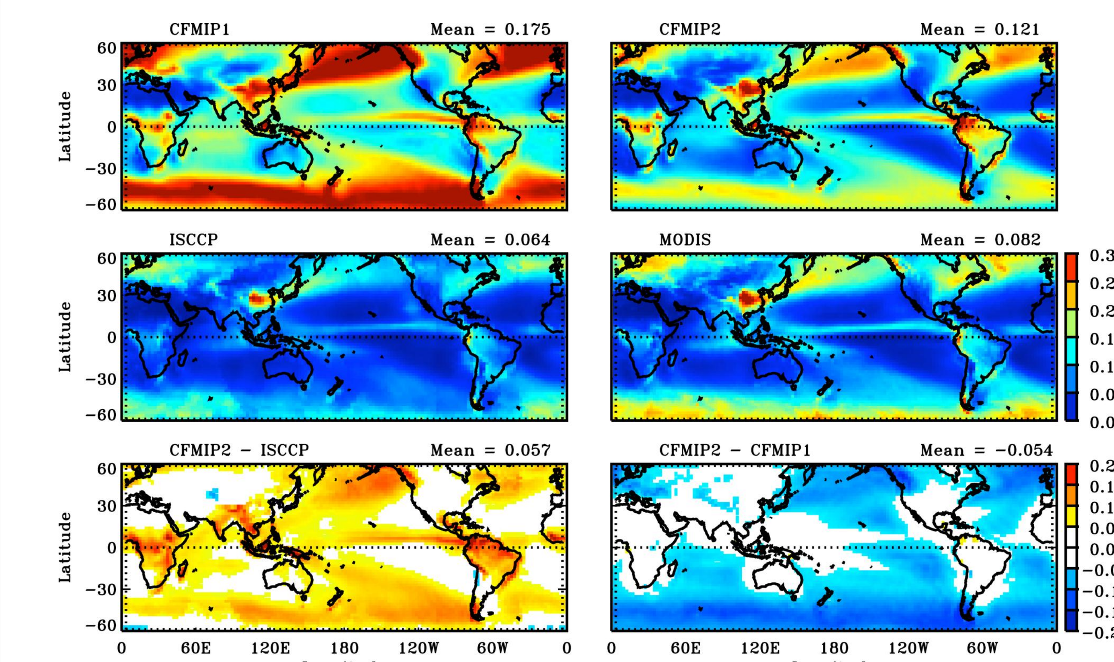
Future Work

- **Using both MME and PPE to address the uncertainties of model simulations and predictions**

MME (multi-model ensembles) –
help to *understand uncertainties from fundamental structural choices*



Total cloud amount (τ > 1.3) from CFMIP1 and CFMIP2 multi-model means, ISCCP and MODIS observations, and the difference of CFMIP2 multi-model mean to the ISCCP and CFMIP1 multi-model mean. ***(Figure 1 from Klein et al., 2012)***



Maps of fractional area covered by optically thick clouds (τ > 23). ***(Figure 5 from Klein et al., 2012)***

PPE (perturbed-parameter ensembles) –
help to understand uncertainties from simplified parameterizations with a single model structure

Our future work will make an effort through combining the two approaches to address the uncertainties of model simulations and predictions

- **Improving COSP to evaluate modeled clouds:**
  - **modify subcolumn precipitation distribution**
  - **Add a function to identify mixed-phase clouds from radar and lidar signals**

These improvements will make it possible for a more meaningful comparison of model simulations to observations, and ultimately help to reduce uncertainty in models.

References:

Zhang, et al., 2012: Regional assessment of the parameter-dependent performance of CAM4 in simulating tropical clouds. Geophys. Res. Lett., doi: 10.1029/2012GL052184.

Klein et al., 2012: Are climate model simulations of clouds improving? An evaluation using the ISCCP simulator. Submitted to JGR.

Acknowledgments:

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